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The Response of Industrial Production to the Price of Oil: New Evidence for Thailand

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Abstract. This paper examines the oil price-industrial production nexus in Thailand by using multivariate cointegration test. In addition, Granger causality is also used to examine the impact of oil price uncertainty on industrial production growth. The main focus of this paper is on one sector of the economy, i.e., manufacturing sector. Monthly data from 1993 to 2015 are utilized. Empirical results reveal that there is a long-run relationship between industrial production and real oil price and other variables. Industrial production adjusts rapidly to shocks to lending rate, price level and oil price. Furthermore, there exists long-run causality running from lending rate, price level and oil price to industrial production. However, industrial production growth does not respond to oil price shock and oil price uncertainty. Asymmetric and nonlinear relationship between oil price shock and industrial output growth is not found. These findings give some policy implications.
Keywords. Industrial production, Oil price shock, Oil price volatility, Cointegration, Causality.
JEL. C22, Q43.

1. Introduction

From theoretical point of view, an increase in oil price should adversely affect output while a decrease in oil price should induce an expansion of output. An oil price shock can be defined as a rise or a fall in the price of oil that can affect macroeconomic variables (see Hamilton, 1983; Mork, 1989 and Hooker, 1996). Most empirical studies on the relationship between oil price shocks and macroeconomic variables seem to support the oil-real activity nexus. An oil shock might have different impacts on different economies due to different characteristics. Recently, many empirical research works find evidence on the negative relationship between economic activity and the price of oil in industrialized countries. A rise in oil price can cause production cost to increase, and thus lower future output growth.

There exists an argument that an oil price shock is likely to have greater impact on real output. An oil price shock can also reflect both the unanticipated component and the time-varying conditional variance component. The volatility component exerts a significant impact on output growth (see Lee *et al.,* 1995). In other words, it is possible that oil price shocks can cause uncertainty in the price of oil, and that oil price volatility can harm output.

The present paper examines the relationship between the price of oil and industrial output. In addition, it also examine whether oil price volatility exerts any significant impact on the growth rate of industrial production. Thailand is an emerging market economy that is heavily dependent on the imports of crude oil, and thus the economy might be vulnerable to changes in the price of oil. Figure 1 shows the trend in domestic real oil price of Thailand.

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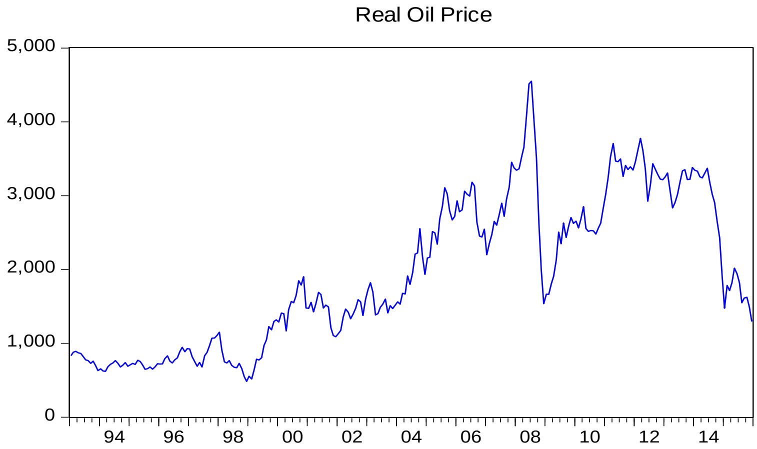

Figure 1. *Domestic Real Oil Price, 1993M1-2015M12*

The rising trend of oil price began from mid-1998 to 2007. The peak of oil price was observed in 2008 due to the surge of world oil prices. The sharp drop in oil price was at the end of 2008. Some oil price fluctuations were observed thereafter. It is possible that fluctuations in oil price can cause oil price uncertainty and that uncertainty can harm industrial production. However, the production in manufacturing sector will be harmed or not depends on the ability of manufacturing firms to adjust their production to oil price fluctuations and oil price uncertainty. Energy efficiency can be used to reduce the cost of production.

The contribution of this paper to the existing literature is as follows. Firstly, monthly data for the period 1993M1-2015M12 are used in the analysis to extend understanding on the possibility of the existence of linear relationship between oil price and industrial production. Secondly, several techniques can be used to examine the oil price-real activity relationship. Economic activity can be measured by aggregate output such as real GDP or industrial production. This paper uses industrial production as a measure of real activity by relying on the notion that manufacturing production for exports can stimulate real GDP of the country. Furthermore, the international oil price expressed in US dollar per barrel is converted to local currency. The advantage of using local-currency oil price is that it can measure the purchasing power of local manufacturing firms. This paper provides evidence of the long-run negative impact of the price of oil on industrial production in Thailand. In addition, oil price volatility or uncertainty does not Granger cause industrial growth.

The rest of this paper is organized as follows. Section 2 reviews empirical results from previous studies. Section 3 describes the dataset used in this study. Section 4 provides empirical results and some discussion while the last section gives concluding remarks.

2. Previous Studies

Empirical studies have conducted for both advanced and emerging market economies. Evidence on the impact of oil price shocks on economic activity mainly comes from industrialized economies. Since the emergence of the study by Hamilton (1983), numerous studies have conducted to examine the impact of oil prices shocks on real activity. Burbidge & Harrison (1984) use vector autoregressive framework to examine the impact of oil price shocks on macroeconomic variables in five OECD countries. They find that oil price shocks impose a negative impact on industrial output growth in these economies. Hooker (1996) finds strong evidence indicating that oil prices no longer cause many of the US macroeconomic variables after 1973. Oil prices are endogenous. Furthermore, linear and symmetric specifications cannot represent the form of oil price interaction with other variables. However, Hamilton (1996) indicates that the US data are consistent with the historical correlation between oil shocks and recession. Federer (1996) finds the negative impact of oil price shocks on key macroeconomic variables in the US and this negative relationship can be explained by the economy's response to oil price volatility. Gronwald (2008) examines the impact of large oil price hikes on the US GDP growth and finds that this impact is distributable to the three large oil price hikes in 1973-74, 1979 and 1991. Similar study by Gosh *et al.,* (2009) also shows the finding that oil price shocks reduce GDP growth in the US. Rahman & Serletis (2011) find that oil price uncertainty imposes a negative effect on the US output. Recent study by Gadea (2014) investigates the relationship between oil price shocks, economic growth and inflation in the US for different periods and finds evidence indicating that GDP growth affect oil price movements and that there is no influence of oil price shocks on GDP growth in the latest oil price episode.

Recently, nonlinearity in the oil price-output relationship has been well established (Kilian & Vigfusson, 2011, and Hamiton, 2011). Earlier study by Cunado & de Gracia (2003) that examines the impacts of oil prices on inflation and industrial production indexes for some European countries gives evidence showing that oil prices have short-run and asymmetric effects on industrial production growth. Jemenez-Rodriguez & Sanchez (2005) examine the effects of oil price shocks on real economic activity of OECD countries. They find evidence of a nonlinear impact of oil price shocks on real GDP growth even though the relationship between oil price shocks and real GDP growth is different among these industrialized countries. Herera *et al.,* (2011) examine asymmetric and nonlinear feedback from the real price of oil to the US industrial production and its sectoral components. They find that such a feedback is sensitive to the estimation period. There is no evidence of asymmetric response at the aggregate level, but there are strong asymmetries at the disaggregate level, especially for industries that are energy-intensive in production. Kim (2012) examines the non-linear relationship between oil prices change and GDP growth using the panel data of industrialized countries and find evidence of nonlinear relationship.

For Asian economies, Cunado & Perez de Gracia (2005) examine the oil prices-macroeconomy relationship by looking at the impact of oil price shocks on both inflation and economic growth rates for some Asian countries over the period 1975-2002. Their main findings are that there is no cointegration between oil prices and economic activity in these countries. This implies that the relationship is just a short-run phenomenon. The results of Granger causality test show that oil price shocks cause economic growth rates in Japan, South Korea and Thailand when oil prices are defined in local currency. In addition, evidence of asymmetry in oil price shocks-economic growth relationship is found only in the case of South Korea. However, Zhang (2008) examines the relationship between oil price shock and economic growth in Japan by using a nonlinear approach and finds the asymmetric effects of oil price shocks on economic growth. Du *et al.,* (2010) use monthly data to investigate the relationship between the world oil price and China's macro-economy. They find that the world oil price significantly affects economic growth and inflation in China. The impact is nonlinear.[1] Park *et al.,* (2011) use a structural vector autoregressive model to examine the impacts of oil price shocks on regional industrial production in South Korea. They find both short- and long-term response of industrial production and price level to oil price shocks. Cunado *et al.,* (2015) employ a structural vector autoregressive model to investigate the macroeconomic impact of structural oil shocks in four of top oil-consuming Asian economies, namely Japan, South Korea, India and Indonesia. They find that economic activities and price levels in these four Asian countries respond differently to oil price shocks, depending on the specific characteristics of each country. Gupta & Goyal (2015) examine how oil price fluctuations affect the Indian economy

[1] Wei (2013) also finds evidence of nonlinear relationship between oil prices and other variables such as industrial production and consumer price indexes at the low frequency domain in Japan.

through various channels. The finds that oil prices is pro-cyclical to output, price level and other variables.

Most previous empirical studies tend to suggest asymmetry and nonlinearlity in investigating the relationship between oil price shock and economic growth. Only few studies produce evidence supporting cointegration and symmetric relationship. However, further research needs to be conducted because country specifics and time period of investigation might matter.

3. Data and Methodology

This section describes the data and the estimation methods that are used in the analysis.

3.1. Data

Monthly data used in this study are obtained from various sources and consist of 276 observations. The series of industrial production index, lending interest rate, consumer price index, and US dollar exchange rate are retrieved from the Bank of Thailand website. The Brent crude oil price series expressed in dollar per barrel is obtained from the US Energy Information Administration. The dataset covers the period from January 1993 to December 2015. The real oil price series is by multiplying crude oil price by the US dollar exchange rate and deflating by the consumer price index. All series are transformed to logarithmic series. The unit root test for stationarity used in this paper is the KPSS test proposed by Kwiatkowski, Phillips, Schmidt & Shin (1992), which is the powerful unit root testing procedure. The results are reported in Table 1.

The variables in Table 1 are defined as follows: y is the log of industrial production index, r is the log of lending rate, p is the log of consumer price index, and op is the log of real oil price series. The KPSS test statistic of each variable in level is larger than the 5% critical value, and thus the null hypothesis that each series is stationary is rejected. In other words, each series contains unit root. For first difference of each series, the KPSS test statistic is smaller than the 5% critical value. Therefore, the null hypothesis that the first difference of each series is stationary cannot be rejected. It can be concluded that each variable is integrated of order 1 or each series is I(1) series because it contains one unit root in level, but not in its first differences.

Table 1. *KPSS unit root testing results*

Variables in levels		
	intercept	intercept and trend
y	1.902 [14]	0.228 [13]
r	1.170 [14]	0.303 [14]
p	1.886 [14]	0.207 [14]
op	1.617 [14]	0.267 [13]
Variables in first differences		
Δy	0.198 [40]	0.094 [43]
Δr	0.127 [11]	0.082 [11]
Δp	0.504 [7]	0.079 [6]
Δop	0.179 [1]	0.086 [1]
Critical value at the 5% level	0.463	0.086

Note: Optimal bandwidth in bracket.

3.2. Estimation Methods

In order to examine the long-run relationship between industrial production and its explanatory variables, namely lending rate, price level and real oil price, this paper makes use of Johansen (1991) cointegration test in a multivariate framework. The model used in this paper is presented in the reduced from in equation (1) as the following:

$$\Delta X_t = C + \Gamma_1 \Delta X_{t-1} + \Gamma_2 \Delta X_{t-2} + ... + \Gamma_p \Delta X_{t-p} + \alpha\beta^{/} X_{t-1} + e_t \qquad (1)$$

$X_t^{/} = [y_t r_t p_t op_t]^{/}$

where y_t is the industrial production, r_t is the lending rate, p_t is the price level, and op_t is the real oil price. The matrix Γ_i, i=1,2,….p is the matrix of short-run parameters, $\alpha\beta^{/}$ is the information on the *coefficient* matrix between levels of the series, and e_t is the vector of the error terms.[2] All crises dummy variables are not included in equation (1) because these crises will affect the dollar exchange rate, which is used to convert the international oil price to the domestic oil price. The existence of cointegration reveals that there is a long-run equilibrium relationship between industrial production and the three explanatory variables.

In case of the existence of cointegration, the error correction mechanism (ECM) is used to examine the short-run dynamics between a change in industrial production, a change in lending rate, inflation rate and a change in real oil price. The ECM is expressed in Eq. (2) as the following:

$$\Delta y_t = \phi_0 + \sum_{i=1}^{k}\phi_{1i}\Delta y_{t-i} + \sum_{i=}^{k}\phi_{2i}\Delta r_{t-i} + \sum_{i=1}^{k}\phi_{3i}\Delta p_{t-i} + \sum_{i=1}^{k}\phi_{4i}\Delta op_{t-i} + \lambda e_{t-1} \qquad (2)$$

where e_{t-1} is the error correction term (ECT), which is the lagged value of the corresponding error term obtained from the estimate of cointegrating relation expressed in Eq. (1).[3]

The negatively significance of the estimated coefficient of the ECT (λ) indicates that any deviation from the long-run equilibrium relationship will be rapidly corrected. Furthermore, one can use the Wald coefficient restriction test can be used to test for long-run and short-run causality between industrial output and lending rate, price level and real oil price variables (see Oh & Lee, 2004). The null hypothesis $H_o : \lambda = 0$ is tested for long-run causality running from the three independent variables to industrial production. In addition, the null hypothesis $H_o : \phi_{1i} = \phi_{2i} = \phi_{3i} = \phi_4 = 0$ is tested for short-run causality.

This paper also examines the impact of oil price volatility on industrial production. The reason behind the investigation is that oil price shocks can generate oil price volatility or uncertainty, which in turn affects output. To achieve this goal, the exponential generalized autoregressive conditional heteroskedastic (EGARCH) model proposed by Nelson (1991) can be used. The volatility model is presented in equations (3) and (4) as follows:

$$\Delta y_t = \mu + \sum_{i=1}^{p} b_i \Delta y_{t-i} + v_t \qquad (3)$$

$$\log(\sigma_t^2 = \alpha + \beta\log(\sigma_{t-1}^2) + \gamma\frac{v_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \phi\left|\frac{v_{t-1}}{\sigma_{t-1}^2}\right| \qquad (4)$$

where $\{v_t\}$ is a sequence of independent and normally distributed random variables with mean of zero and variance of 1. Equation (3) is the mean equation, which is assumed to follow an autoregressive mode of order p or AR(p) process. Equation (4) is the conditional variance equation with asymmetric effect if the

[2] The relevant elements of the matrix α are adjusted coefficients and the matrix β contains the cointegrating vector. Johansen & Juselius (1990) explain that there are two likelihood ratio test statistics to test for the number of cointegrating vectors. The two tests are the trace test and the maximum eigenvalue test. In addition, the two test statistics can be compared with the critical values to determine whether cointegrating vectors exist.

[3] The main focus of the paper is to investigate how industrial production responds real oil price. Therefore, only ECM equation is presented.

coefficient γ is non-negative. The advantage of using the AR(p)-EGARCH(1,1) specification is that it does not impose the non-negativity constraint on the parameters in the conditional variance equation.

The Granger causality test can be used to test for causations between the change in industrial production, an oil price shock and oil price volatility. In particular, this paper aims at testing the null hypothesis that oil price volatility causes the change in industrial production. Furthermore, whether oil price uncertainty causes oil price shocks or oil price shocks causes oil price uncertainty needs to be explored.

4. Empirical Results

In this section, the results from cointegration tests, the impact of oil price volatility and asymmetric and nonlinear relationship between oil price shock and industrial output growth are reported.

4.1. Cointegration and Short-Run Dynamics

Based on the unit root test results reported in Table 1, all series in this paper are I(1) series. Therefore, it is appropriate to test for cointegration by using Johansen's methodology in a multivariate framework. The results of cointegration test using the optimal lag of 1 determined by Schwarz criterion (SC) are reported in Table 2.

The results in Table 2 show that there are 4 cointegrating vectors in the trace test while the maximum eigenvalue test indicates only 2 cointegrating vectors.

Table 2. *Johansen's cointegration test*

Panel A. Trace test.			
No. of cointegrating vectors	Trace statistic	5% Critical value	p-Value[b]
None[a]	68.710	47.861	0.000
At most 1[a]	30.493	27.797	0.042
At most 2[a]	16.053	15.595	0.041
At most 3[a]	4.548	3.841	0.033
Panel B. Maximum eigenvalue test.			
No. of cointegrating vectors	Max-eigenvalue statistic	5% Critical value	p-Value[b]
None[a]	38.217	27.584	0.002
At most 1	14.440	21.132	0.330
At most 2	11.506	14.265	0.131
At most 3[a]	4.548	3.841	0.033

Note: [a] denotes the rejection of the null hypothesis of no conintegration at the 5% level.
[b] denotes p-value provided by MacKinnon et al. (1999).

Based upon the results of the two tests, it can be concluded that the first cointegrating vector is precisely confirmed.[4] Based upon the results reported in Table 2, it can be argued that there exists a stable long-run relationship between industrial production and its explanatory variables, namely lending rate, price level and real oil price in Thailand. The estimated long-run coefficients of the cointegrating equation are shown in Table 3.

Table 3. Estimated long-run coefficients

Dependent variable: y_t		
Independent variable	Long-run coefficient	t-statistic
r_t	-0.807	-4.767***
p_t	2.457	7.743***
op_t	-0.504	-3.973***

Note: *** indicates significance at the 1% level.

The results in Table 3 suggest that lending rate from financial institutions, price level, and real oil price have a strong and statistically significant impact on Thailand's industrial output. A one percent increase in the lending interest rate

[4] The order of variables entering into the unrestricted VAR model is y_t, r_t, p_t and op_t respectively. The first cointegrating equation indicates that y_t is dependent variable while r_t, p_t and op_t are independent variables in the long-run equilibrium relationship.

causes industrial output to fall by 0.81 percent. However, inflation measured as a change in the consumer price index positively related to industrial production, i.e., a one percent increase in inflation will cause industrial output to rise by 2.46 percent. For the real price of oil, a one percent increase in real oil price causes industrial production to drop by 0.5 percent. Therefore, it can be argued that there is a statistically negative response of industrial production to real oil price. This finding is not in line with the finding by Cunado & de Gracia (2005) that utilize quarterly data and real GDP as a measure of economic activity.

The presence of cointegrating relation suggests that this relationship can be efficiently represented by ECM corresponding to equation (1) as presented in equation (2). The estimate of equation (2) gives the short-run dynamics reported in Table 4.

Table 4. Short-run dynamics

Dependent variable: Δy_t		
Independent variable	Short-run coefficient	t-statistic
Δy_{t-1}	-0.175	-3.001***
Δr_{t-1}	-0.196	-1.774*
Δp_{t-1}	1.193	2.454**
Δop_{t-1}	0.029	1.034
ECT	-0.025	-2.038**
intercept	0.001	0.484

Note: ***, **, and * indicate significance at the 1%, 5% and 10%, repectively.

Based upon the estimate of Eq. (2), the estimated coefficient of the ECT is significantly negative and has the absolute value of less than 1. This suggests that Thailand's industrial production adjusts to its long-run equilibrium at a rapid rate. This also suggests that the estimated ECM equation is found to be stable. In the short run, the impact of a change in lending rate on a change in industrial production is negative and significant at the only 10% level while the impact of a change in price level on a change in industrial production is positive and significant at the 5% level. However, there is no short-run impact of a change in oil price or oil price shocks on a change in industrial production. In Granger causality sense, there can be the long-run causality when cointegration among variables exists. The results reported in Table 4 represent the autoregressive model augmented with the ECT. The Wald test is used to examine whether the coefficient of the ECT is zero. The Wald F-statistic of 5.44 with the p-value of 0.021 rejects the null hypothesis of no long-run causality. Therefore, it can be argued that there is long-run causality running from lending rate, price level and oil price to industrial production.[5] Furthermore, the joint test for short-run causality gives the Wald F-statistic of 3.671 with the p-value of 0.013 rejects the null hypothesis that there is no short-run causality running from the three variables to industrial production. Even though the joint test indicates short-run causality, the estimated coefficient of lagged oil price shock is not significant. Therefore, it can be concluded that there no short-run causality running from oil price shock to industrial output growth.

The impulse response functions shown in Figure 2 can be used to trace the time path of the impact of structural shocks to industrial production in response to a nit change in shocks to lending rate, price level and oil price. A positive unit shock to lending rate contributes to a permanent decrease in industrial production, but a positive unit shock to price level contributes to an initial increase in industrial production for two months and a decrease at a slowing rate, which does not dissipate. However, the time path of the impact of oil price shock is different, i.e., a positive unit shock to oil price causes industrial production to initially increase, but shows a permanent decrease after four months.

[5] See Granger (1988).

It is possible that oil price shock or a change in the price of oil can cause oil price uncertainty. The results of from estimation of volatility model specified in equations (3) and (4) are reported in Table 5.

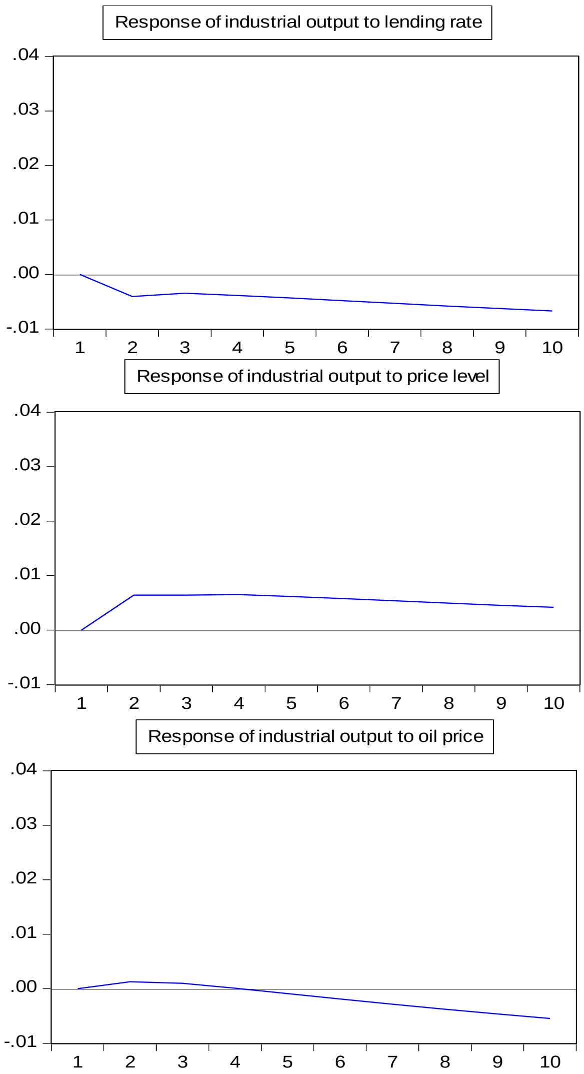

Figure 2. *Impulse response functions*

4.2. Impact of Oil Price Volatility

The important questions are that (1) does oil price shock cause oil price uncertainty? and/or does oil price uncertainty cause oil price shock? and (2) do an oil price shock and oil price uncertainty cause industrial output?. The AR(1)-EGARCH(1,1) model is chosen and estimated to generate the oil price uncertainty series. In addition, the standard Granger causality test is conducted to test for causality. The estimate of AR(1)-EGARCH(1,1) model expressed in equations (3) and (4) is reported in Table 5.

Table 5. Estimate of the AR(1)-EGARCH(1,1) model

Panel A: Mean equation with dependent variable r_t			
Variable	Coefficient	t-Statistic	p-Value
r_{t-1}	0.186***	2.693	0.007
Intercept	-0.002	-0.408	0.683
Panel B: Conditional variance equation with dependent variable $\log(\sigma_t^2)$.			
Variable	Coefficient	t-Statistic	p-Value
$\log(\sigma_{t-1}^2)$	0.913***	15.782	0.000
$v_{t-1}/\sqrt{\sigma_{t-1}^2}$	-0.084	-1.366	0.172
$\lfloor v_{t-1}/\sigma_{t-1}^2 \rfloor$	0.313***	2.724	0.006
Intercept	-0.679**	-2.023	0.043
Panel C: Diagnostic tests.			
Q(4) = 2.272 (p-Value = 0.686), Q(12) = 13.348 (p-Value = 0.344).			
Q^2(4) = 2.361 (p-Value = 0.670), Q^2(12) = 15.765 (p-Value = 0.202).			

Note: *** and ** denote significance at the 1% and 5% level.

In Panel A of Table 5, the coefficient of the first autoregressive term, r_{t-1}, is positive and statistically significant. In Panel B of Table 5, all coefficients in the conditional variance equation are statistically significant, except for the coefficient of asymmetry, $v_{t-1}/\sqrt{\sigma_{t-1}^2}$. The residual diagnostic tests for this model in Panel C of Table 5 show that the null hypothesis of no residual correlation is accepted by the Ljung-Box test statistics, Q(4) and Q(12). In addition, the null hypothesis of no further ARCH effect is also accepted by the Q^2(4) and Q^2(12). Therefore, it can be argued that the model fits the data quite well. The generated oil price volatility is plotted in Fig. 3.

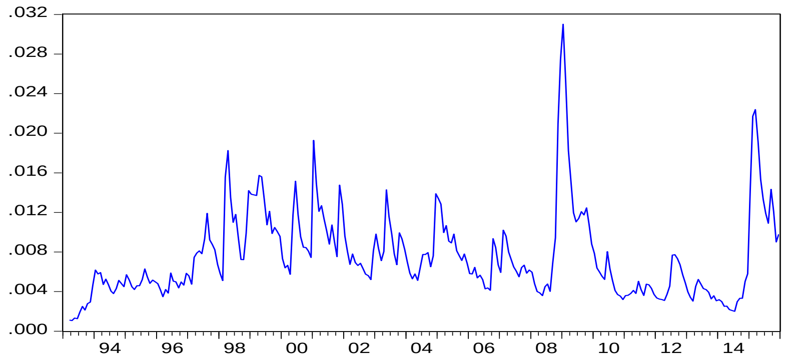

Figure 3. *Oil price volatility or uncertainty.*

Figure 3 shows the plots of uneven oil price uncertainty. Oil price uncertainty appears to be less fluctuating until the adoption of the flexible exchange rate regime in July 1997. In addition, the new oil price shocks in 2000 cause the higher uncertainty that lasts until 2009. However, a decline in crude oil price causes a drop in its uncertainty in 2010.

The standard Granger causality test results using the optimal lag of 1 determined by SC are reported in Table 6.

Table 6. *Grange causality.*

Null hypothesis	F-statistic	p-Value
Oil price shock does not cause oil price uncertainty.	124.67***(+)	0.00
Oil price uncertainty does not cause oil price shock.	5.85**(-)	0.02
Oil price shock does not cause industrial production growth.	2,58 (+)	0.11
Oil price uncertainty does not cause industrial production growth.	0.049 (-)	0.82

Note: *** and ** denote significance at the 1% and 5% level.
+ and – denote positive and negative impact.

The results in Table 6 reveal that the null hypotheses that oil price shock does not cause industrial production growth and that oil price uncertainty does not cause industrial production growth are accepted. Therefore, oil price shock does not affect industrial growth in the short run is consistent with the result reported in Table 4. In addition, oil price uncertainty does not promote or harm industrial growth. This finding does not support the finding by Lee *et al.* (1995). However, the null hypotheses that oil price shock does not cause oil price uncertainty and that oil price uncertainty does not cause oil price shock are rejected at the 1% and 5% level, respectively. Therefore, there is bidirectional causality between oil price shock and oil price uncertainty. Even though oil price shock causes oil price uncertainty to increase and oil price uncertainty causes a fall in oil price shock. It does not necessarily imply that oil price will not impose a negative effect on industrial production in the long run.

4.3. Asymmetry and Nonlinearity in Oil Price Shock-Output Growth Nexus

Asymmetric and nonlinear relationship between oil price shock and industrial output growth is tested to confirm the results of short-run relationship.

The simple method that is used to test for asymmetric effects of oil price shock on industrial output growth is expressed as the following equation:

$$\Delta y_t = \alpha_0 + \alpha_1 \Delta op(+)_t + \alpha_2 \Delta op(-)_t + \Delta y_{t-1} + u_t \qquad (5)$$

where $\Delta op(+)$ denotes positive oil price shock and $\Delta op(-1)$ denotes negative oil shock. The inclusion of lagged industrial output growth can correct for autocorrelation. In equation (5), oil price shocks are decomposed into positive and negative components (Mork, 1989). If an asymmetric impact exists, the two coefficients of positive and negative shocks should be significantly different from zero with different sizes. The results from the estimate of equation (5) are reported in Table 7.

Table 7. *Asymmetric Relationship.*

Dependent Variable: Δy_t				
Variable	Coefficient	Std.Deviation	t-Statistic	Prob.
$\Delta op(+)_t$	0.013	0.082	0.156	0.877
$\Delta op(-)_t$	0.045	0.067	0.683	0.496
Δy_{t-1}	-0.065	0.061	-1.264	0.289
intercept	0.507	0.546	0.929	0.353

Note: $\Delta op(+)$ denotes positive oil price shock,
$\Delta op(+)$ denotes negative oil price shock.

The results in Table 7 show that the coefficients of positive and negative oil price shocks have a positive sign, but are not statistically significant. This indicates that the absence of the asymmetric impacts of oil price shock industrial output growth. This finding is in line with the results found by Cunado & Perez de Gracia (2005).

For nonlinearity test, the nonlinear model proposed by Hansen (1999) can be used to detect the threshold level of oil price increases that can harm industrial output growth. The threshold model that can detect nonlinear relationship between oil price shock and industrial production growth is based on the following equation:

$$\Delta y_t = \beta_0 + \beta_1 \Delta op_t + \beta_2 D_t (\Delta op_t - k) + \varepsilon_t \qquad (6)$$

where k denotes the threshold level of oil price shock that produces the nonlinear negative relationship between oil price shock and industrial output growth. The dummy variable takes the value of 1 if oil price shock is above k

percent and zero otherwise. The estimated results of equation (6) are reported in Table 8.[6]

Table 8. *Threshold Level of Oil Price Shock*

Dependent Variable: Δy_t					
k	Variable	Coefficient	Std.Deviation	t-Statistic	Prob.
4%	Δop_t	0.026	0.054	0.475	0.635
	$D_t(\Delta op_t\text{-k})$	0.015	0.143	0.102	0.919
	Intercept	0.375	0.413	0.907	0.365
6%	Δop_t	0.022	0.050	0.437	0.602
	$D_t(\Delta op_t\text{-k})$	0.041	0.160	0.257	0.797
	Intercept	0.357	0.381	0.936	0.350
8%	Δop_t	0.021	0.047	0.445	0.328
	$D_t(\Delta op_t\text{-k})$	0.066	0.187	0.353	0.724
	Intercept	0.358	0.365	0.981	0.328

Note: The threshold level of oil price shock, k, is tested at 4, 6 and 8 percent.

The p-values of the estimated coefficients are high, which show that oil price shock does not affect industrial output growth at all values of k parameter. These results are consistent with the result of no short-run causality running from oil price shock to industrial output growth. Furthermore, the insignificant coefficients of the threshold variables indicate that there is no nonlinear relationship between inflation and output growth.

5. Concluding Remarks

This paper investigates the oil price-industrial production relationship in Thailand using monthly data from 1993 to 2015. The real oil price series is measured in local currency. The methods employed in this paper are Johansen's cointegration and Granger causality tests. In addition, an oil price shock can cause oil price uncertainty. Therefore, the AR(1)-EGARCH(1,1) model is used to generate the uncertainty series. The impacts of an oil price shock and its uncertainty are examined by using the causality test. The main findings can be summarized as follows. First, industrial production is cointegrated with oil price along with lending rate and price level. The significant coefficient of the error correction term indicates that there is a stable long-run relationship between economic activity in a manufacturing sector and the real price of oil. Second, the impact of an oil price shock on industrial production growth is not observed in the short run. Third, there is no asymmetry and nonlinear relationship between oil price shock and output growth. Finally, oil price uncertainty does not affect industrial production growth. Policy implication based on the findings in this paper is that energy efficiency as well as alternative energy sources deem necessary for the long-run growth of the country.

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[6] Since the threshold parameter (k) is assumed to be known, the ordinary least squares method can be used.

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